

25 **Abstract**

26 There is a strong body of evidence that patterns of collective behaviour in
27 grouping animals are governed by interactions between small numbers of
28 individuals within the group. These findings contrast with study of the ‘selfish
29 herd’, where increasingly complex individual-level movement rules have been
30 proposed to explain the rapid increase in aggregation observed when prey
31 groups are startled by or detect a predator. While individuals using simple rules
32 take into account the position of only a few neighbours, those using complex
33 rules incorporate multiple neighbours, and their relative distance, to determine
34 their movement direction. Here, we simulate the evolution of selfish herd
35 behaviour to assess the conditions under which simple and complex movement
36 rules might evolve, explicitly testing predictions arising from previous work. We
37 find that complex rules outperform simple ones under a range of predator attack
38 strategies, but that simple rules can fix in populations particularly when they are
39 already in the majority, suggesting strong positive frequency dependence in rule
40 success. In addition, we explore whether a movement rule derived from studies
41 of collective behaviour (where individuals use the position of 7 neighbours to
42 determine movement direction) performs as successfully as more complex rules,
43 finding again positive frequency dependence in rule success, and a particular
44 role for predator attack strategy (from within or outside the group).

45

46 **Introduction**

47 Aggregation into groups is a widely observed natural-history trait, both
48 taxonomically and across different biomes. An understanding of the selective
49 pressures underlying animal grouping behaviours has been a dominant feature
50 throughout the study of behavioural ecology (all four editions of the seminal
51 textbook 'An Introduction to Behavioural Ecology' devote a whole chapter to the
52 phenomenon; e.g. Davies et al. 2012). Aggregation often considered to arise as a
53 response to predation (Krause and Ruxton 2002; Wood and Ackland 2007), as it
54 carries with it a number of anti-predator benefits, including increased vigilance
55 (e.g. Roberts 1996), dilution (reduced chance of being the individual attacked;
56 Foster and Treherne 1981), encounter-dilution (reduced encounter rate; Turner
57 and Pitcher 1986) and confusion effects (cognitive limitations reducing success;
58 Miller 1922; Krakauer 1995), which act to reduce individual risk to each group
59 member.

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61 Individuals within groups also benefit from the mechanisms outlined by the
62 selfish herd hypothesis (Hamilton 1971), where individuals reduce their own
63 risk of predation at the expense of others in the group, effectively seeking cover
64 within the group and placing other group members at increased risk. Work on
65 selfish herds focuses primarily on the behavioural strategies ('movement rules')
66 of individuals that generate aggregations, to explain the oft-observed
67 phenomenon of facultative or increased aggregation in response perceived
68 threat (Hamilton 1971; Foster and Treherne 1981; Krause and Tegeder 1994;
69 Watt et al. 1997; Spieler and Linsenmair 1999; Viscido and Wetthey 2002).

70

71 Perceived threat can also increase synchrony within groups (Bode et al. 2010).
72 The synchronous behaviour of large aggregations has been the focus of
73 significant research effort, in an attempt to understand how large-scale collective
74 behaviour can be brought about through interactions between individuals.
75 Theoretical (e.g. Huth and Wissel 1992; Huth and Wissel 1994; Couzin and
76 Krause 2003; Giardina 2008; Hildenbrandt et al. 2010; Bode et al. 2011a) and
77 empirical (e.g. Buhl et al. 2006; Ballerini et al. 2008a; Katz et al. 2011) evidence
78 suggests that patterns of collective behaviour in grouping animals are governed
79 by interactions between small numbers of individuals within the group. For
80 starling flocks, for example, each individual interacts with 6 or 7 neighbours on
81 average (Ballerini et al. 2008a); models incorporating interactions over similar
82 topological distances confirm collective behaviour as an emergent property of
83 the system (Hildenbrandt et al. 2010; Bode et al. 2011a; Bialek et al. 2012). Pair-
84 wise interactions in fish shoals effectively capture spatial patterns in groups of
85 up to 30 individuals (Katz et al. 2011), and locust swarms are coordinated by
86 only by short-range local interactions within a range of 13.5cm (Buhl et al. 2006).
87
88 This focus on generating large scale patterns from interactions with small
89 numbers of neighbours contrasts sharply with the study of selfish herd
90 behaviour, where research has focused on identifying movement rules that
91 result from complex interactions between increasingly large numbers of
92 neighbours (Morton et al. 1994; Viscido et al. 2002; Reluga and Viscido 2005).
93 Evolutionary simulations of selfish herds suggest that populations become
94 dominated by individuals that account for the position of much larger numbers
95 of neighbours (Reluga and Viscido 2005), but empirical evidence for selfish herd

movement rules is limited. Sticklebacks move towards a neighbour that can be reached more quickly, rather than one that is geographically closer (Krause and Tegeder 1994), and seals' movement is consistent with attraction towards a single neighbour (using simple rules) rather than multiple neighbours (De Vos and O'Riain 2012). In contrast, sheep movement patterns in response to threat from a sheepdog are consistent with the idea that they are moving towards the group centre (King et al. 2012).

A key difference between these two areas of work is that while collective behaviour represents a stable level of aggregation, the selfish herd is a process of (increasing) aggregation levels. However, theoretical research on the selfish herd focuses primarily on the point at which stable aggregations have formed, but recent work suggests that timing of predator attacks in relation to the point at which prey first detect the predator and initiate anti-predator behaviour is crucial in determining the success of movement rules, and that simpler rules, accounting for fewer neighbours, might evolve under a range of biologically-plausible conditions (Morrell and James 2008; Morrell et al. 2011a). While it is of course feasible that the different situations of movement synchronisation and increasing aggregation use different methods of processing information, the discrepancy in research activity is worthy of further investigation.

In our previous work, we found that simpler mutant aggregation strategies (rules) experienced a reduced share of the risk in populations of more complex rules, when predators attacked during the process of aggregation (Morrell et al. 2011a), and in populations that are of lower density (Morrell et al. 2011b) and

larger size (Morrell & James 2008). More complex rules are more effective at reducing risk in larger and denser populations (Morrell & James 2008, Morrell et al. 2011b) and when predators attack later in the movement sequence (Morrell et al. 2011a). Complex rules are also more effective at moving individuals from the periphery of a group to the centre (Morrell et al. 2011b), where they will be protected from predators that attack from outside the group (for a discussion of predator attack strategies, see Morrell and Romey 2008; Morrell et al. 2011a and 2011b). We use the terms ‘simple’ and ‘complex’ rules to reflect the terminology used in previous papers in this field. There has been no investigation into whether these rules are cognitively ‘simple’ or ‘complex’ for animals, and this may differ between species (discussed in Morrell and James 2008; Morrell et al. 2011a; 2011b). Essentially more complex rules appear to require individuals to obtain a greater amount of information from their environment in order to apply them.

Our previous work (Morrell & James 2008, Morrell et al. 2011a, b) provides a series of predictions, based on reduction of individual risk in a group, as to when mutant individuals using simpler rules should be able to invade a population of more complex rules. Here, we explicitly test those predictions in an evolutionary simulation model, to explore whether the reduction in risk translates into fixation in a population over evolutionary time. Our first aim, therefore, is to test the following predictions arising from previous work:

1. Predators that attack from the periphery favour the evolution of complex movement rules in prey

2. When predators attack early in the movement sequence (i.e. shortly after they are detected, and when individuals have had little time to move in response to detecting the predator), simple strategies are favoured, while predators that attack later favour the evolution of more complex strategies.
3. Variation in attack timing (i.e. when predators can attack both quickly and more slowly after prey initiate aggregation) should favour the maintenance of mixtures of strategies within the population (following from prediction 2).
4. Simple rules are favoured in large, low-density populations, while complex rules are favoured in small, compact populations.
- Our second aim (which could be considered a special case of the more general aim 1) is derived from the substantial body of work on collective behaviour (e.g. Couzin and Krause 2003; Ballerini et al. 2008a; Giardina 2008; Hildenbrandt et al. 2010; Buhl et al. 2011; Katz et al. 2011; Bode et al. 2011a; Bialek et al. 2012), and is to specifically assess whether a rule whereby individuals move towards 7 neighbours might perform as effectively as more complex rules in reducing individual risk. This leads to the prediction that:
5. A rule whereby individuals account for the position of 7 neighbours (i.e. a relatively small number) is as likely to evolve as a more complex rule whereby individuals account for the position of up to 20 individuals (the “Local Crowded Horizon” rule; Viscido et al. 2002, table 1).

Materials and Methods

We used an agent-based modelling framework used in previous work on selfish herd behaviour (James et al. 2004; Morrell and James 2008; Morrell et al. 2011b; Morrell et al. 2011a) as the basis for our evolutionary simulation. In each generation of the model, N point-like agents representing the prey individuals are randomly placed (following a uniform random distribution) into a circular arena of radius R m, giving a prey density $d = N/\pi R^2$. We assume that the habitat is homogeneous and provides no areas of cover that could be used to reduce predation risk: in accordance with (Hamilton 1971), cover is provided by position relative to other individuals only, and prey receive no directional information regarding predatory threat (Hamilton 1971; Morton et al. 1994; Viscido et al. 2002; James et al. 2004; Morrell and James 2008; Morrell et al. 2011b; Morrell et al. 2011a). We consider $N = 20$ and $d = 4$ as our ‘baseline’ parameter values, and explore the independent effects of increasing group size ($N = 50$) and increasing density ($d = 10$).

Each prey is allocated a movement rule, selected from those previous proposed. We consider 4 movement rules here, following previous work on the topic. Firstly, we consider the 3 rules investigated by Morrell et al. (2011a) and Morrell et al. (2011b): nearest neighbour (NN), 3 nearest neighbours ($3NN$) and local crowded horizon (LCH). These rules are described in table 1. To investigate whether rules that account for 7 neighbours are competitive against those that account for more (prediction 4), we also include a 7 nearest neighbour rule ($7NN$) in our investigations. Although previous work has considered ‘random movement’ as a potential rule, we do not include it here as it is well established that all other rules are beneficial in relation to random movement (Morton et al.

1994; Viscido et al. 2002; Morrell and James 2008). In each generation, N_p individuals are allocated a 'population' movement rule, and N_m are allocated a 'mutant' movement rule ($N_m + N_p = N$). We explore 2 different starting combinations: a single mutant in a population using a different rule ($N_m = 1, N_p = N-1$), and a situation where both rules begin at equal frequencies ($N_m = N_p = N/2$). These two scenarios represent two possible events: a mutant rule arising by chance in an existing group, and a situation where two groups, using different rules, meet. Throughout, we refer to the 'simpler rule' as the one that requires information about the position fewer neighbours, and the 'more complex rule' as one that require information about more neighbours (table 1).

As in previous work, the start of the simulation (timestep $t = 0$) represents the point in time at which the prey first detect the predator and movement begins. We assume that all individuals detect the predator simultaneously and begin moving, following Hamilton (1971), Morton et al (1994), Viscido et al. (2002) and Morrell and James (2008). The end of the simulation occurs at time T , which is the point at which the predator attacks the prey. In each timestep t ($t=0.1$ s), each prey individual identifies its target location, dependent on its allocated movement rule and moves at a speed of 0.15 m s^{-1} towards the target location (representing the movement speed of a three-spined stickleback, following James et al. 2004). All individuals move simultaneously, and update their target location in each timestep. At time T ($T > 0$) the predator appears, and attacks the closest prey item. T takes either fixed values ($T = 20, 50$ and 100 are used here) or is randomly drawn from a uniform distribution between 0 and T_{max} ($T_{max} = 50, 100$).

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220 We investigate two predation strategies P : the predator may appear within the

221 group (following Hamilton 1971) or may appear outside the group (empirical

222 evidence for these strategies is reviewed in Morrell and Romey (2008) and

223 discussed in Morrell and James (2008) and Morrell et al. (2011a, 2011b) in the

224 context of the selfish herd). If the predator appears within the group, we

225 calculate the mean group centre from the x and y coordinates of the prey at T ,

226 and the maximum distance of all prey from the mean group centre. The predator

227 is placed at random within the circle described by these two parameters,

228 following a uniform distribution. Predators attacking from outside the group

229 appear at the edge of the circular arena (distance R from the arena centre), at a

230 location determined by an angle drawn from a random uniform distribution.

231

232 Once the predator location has been determined, the predator attacks the closest

233 prey item. We assume that an attack always occurs, and that all attacks result in

234 successful predation. The movement rule of the predated individual is recorded.

235 For simplicity, we assume that only one individual is predated, and that

236 individual is replaced in the next generation. To determine the movement rule of

237 the replacement individual, we calculate the proportion of surviving individuals

238 using each rule. If a random number drawn from a uniform distribution between

239 0 and 1 is less than N_m/N , the replacement individual follows the mutant

240 movement rule; otherwise it follows the population movement rule. N_m and N_p

241 are updated in each generation for a total of 5000 generations, or until the

242 population fixes at a single movement rule (N_m or $N_p = N$). This final movement

243 rule is recorded, or, if a mixture of movement rules still remains (N_m and $N_p > 0$),

244 this fact is recorded. For each combination of movement rules, and for each set of
245 parameter values (see below), we ran 1000 replicates to give a final output of the
246 number of replicates ending in each of the three possible outcomes: mutant rule
247 fixes, population rule fixes, and mixture of rules remains. We standardised the
248 starting positions of both prey and predators for each combination of movement
249 rules and set of parameter values (Morrell et al. 2008), such that each set of 1000
250 replicates x 5000 generations was run with the same set of initial positions for
251 both predators and prey.

252
253 We compare the frequency at which each rule becomes fixed against random
254 expectation i.e. the proportion of simulations in which a rule is expected to fix if
255 predation is independent of movement rule (i.e. through drift). The probability of
256 such a 'neutral' mutant rule becoming fixed is equal to its frequency in the
257 population at the start of the simulation (i.e. N_m/N , Kimura 1962). Statistical
258 comparisons between model output and the expected frequency were made
259 using binomial tests (R v2.12.2, R Development Core Team 2011), corrected for
260 multiple testing (180 tests were run) using a Bonferroni correction. These
261 results are displayed on the figures. We found essentially similar results to those
262 represented here when we re-ran the model with different combinations of
263 parameter values caused by different discretization of strategy-space, so can be
264 relatively confident our results are robust in this regard. Our key findings are
265 summarised in table 2.

266
267 In contrast to previous work (Hamilton 1971; Morton et al. 1994; Viscido et al.
268 2002; James et al. 2004; Morrell and James 2008; Morrell et al. 2011b; Morrell et

al. 2011a) we do not explicitly calculate the Domain of Danger (DOD; Hamilton 1971) or limited DOD (LDOD; James et al. 2004) for each individual. This is implicitly captured in our assumption that predators target the nearest individual, as the DOD describes the space around each individual that is closer to it than to any other individual. Thus, when a predator attacks the closest individual, it is by definition within the DOD of that individual.

Results

(a) Invasion success and predator attack strategy

Firstly, we investigated the effect of predator attack strategy (from within the group or from outside it, prediction 1) and fixed attack time T of 20, 50 and 100 timesteps (equivalent to 2, 5 and 10 s, prediction 2) on the proportion of simulations ending with the fixation of each rule. We find that in general, complex populations (groups where the field strategy is complex) are highly stable against invasion by a single simpler mutant (figure 1a, d and g), with only occasional instances of 3NN mutants becoming fixed in LCH populations (figure 1g). Otherwise, successful invasions by simpler rules are consistent with random expectation, or worse. When both rules begin at equal frequencies (figure 1b, e and h), the complex rule is likely to outcompete the simpler one and reach fixation more often than expected by chance. The exception to this is at short attack times when predators attack from within the group, when NN strategies can reach fixation against LCH (figure 1e) at a rate consistent with chance, and 3NN reaches fixation at the expense of LCH (figure 1h). Logically, this is sensible: in a short period of time, an individual moving towards a dense but more distant area of a group makes little immediate progress towards a near neighbour

(remaining isolated for longer), while an individual moving directly to that neighbour reduces its risk rapidly (Morrell and James 2008).

More complex mutants can successfully reach fixation more often than expected by chance in simpler populations (groups where the field strategy is simple) (figure 1c, f and i), but they do not dominate the results, suggesting that simple populations can be stable against single, more complex mutants. This is particularly true when predators attack from the inside, when attack times are shorter, and when the difference in rule complexity is smaller (i.e. NN v 3NN and 3NN v LCH, but less for NN v LCH). At fixed attack times, as expected, we see very few situations where a mixture of rules is maintained in the population: the only instance of this occurring is seen in figure 3h, at $T = 100$ and when predators attack from within the group (see table 2 for a summary).

(b) Fixed versus variable attack timing

Next, we investigate the effect of variable attack timing (where attack timing is drawn from a uniform distribution between 0 and T_{max}) on the fixation of rules (prediction 3). As we previously (figure 1) showed that mixtures might be favoured particularly when groups start with equal frequencies of the two rules, we explore this starting combination here. We find no evidence to suggest that mixtures of rules are maintained in the population when attack time T is variable (i.e. drawn from a random uniform distribution) for any pairwise combination of movement rules at any of the three group size and density parameters we tested (figure 2).

(c) Effects of population size and density

We did, however find that population size and density influenced the success of different rules (prediction 4, figure 2). Increasing the size of the population (comparing the left hand column of figure 2 where $N = 20$ to the central column where $N = 50$) favours simpler rules at short attack times, for NN v LCH (at the shortest attack time $T = 20$) and 3NN v LCH (at attack times $T = 20, T = 50$ and both variable timings, but not at $T = 100$, where LCH is favoured by increasing population size). Simple rules are not favoured by increasing population size for NN v 3NN where 3NN is increasing favoured as group size increases (figure 2b), or for NN v LCH, where LCH remains superior at attack times other than $T = 20$. Increasing the density of the population (right hand column of figure 2) slightly favours the fixation of more complex rules across all rule combinations.

(d) Effectiveness of 7NN

Both 7NN and LCH populations are generally stable against mutants using the alternative rule (prediction 5, figure 3). In LCH populations, 7NN may come to dominate in a small proportion of replicates, especially when predators attack from within the group (figure 3a-c). 7NN populations, on the other hand, are stable except when predators attack from outside the group, when LCH can invade a small proportion of the time (figure 3g-i). Increasing density reduces slightly population stability for both rules (figure 3c and i), but increasing population size benefits only LCH mutants. When the rules begin at equal ratios (figure 3d-f), 7NN fixes in a larger proportion of replicates when predators attack from within the group, while LCH fixes in the majority of simulations when predators attack from outside the group. This is particularly true at increased

population sizes (figure 3e) and differences are less marked in denser groups (figure 3f).

Discussion

A key motivation for our study was a growing apparent incongruity in the literature. On one hand, much of the theoretical literature on behaviours underlying the selfish herd, including our results here, suggests that cognitively more complex behavioural rules generally outperform simpler rules (Viscido et al. 2002; Reluga and Viscido 2005; Morrell and James 2008; Morrell et al. 2011a). On the other hand, empirically based works suggest that in most taxa studied the behaviours that appear to underlie the formation and especially maintenance of groups appear to be relatively simple, involving responsiveness to only a small number of neighbouring individuals (Couzin and Krause 2003; Ballerini et al. 2008b; Ballerini et al. 2008a; Hildenbrandt et al. 2010; Katz et al. 2011; Bode et al. 2011a; Bialek et al. 2012). Here we have been able to offer pointers towards a resolution of this incongruity. In particular we show that the performance of individuals with particular behaviours within a group is strongly positively frequency dependent. Thus under a wide range of the situations explored in this study we find that a mutant with a more complex movement rule can fail to invade a population with a simpler rule, even in circumstances where the complex rule would be evolutionarily stable to reinvasion by the simpler one if it did reach numerical dominance in the population. Hence, if it is the case the simple aggregation-linked movement rules are a common evolutionary intermediate stage in the development of more complex rules, then this strong

positive frequency dependence may mean that initial flourishing of simple rules stops subsequent evolutionary spread of complex rules.

Although the idea that complex aggregation rules evolve from simpler ones is highly plausible (Reluga and Viscido 2005), our results point to the considerable benefit this field would gain from increasing our understanding of the evolution the cognitive underpinning of such rules to test this conjecture. Little is known about the relative costs of the different rules in relation to their apparent complexity. Complex rules may carry cognitive costs associated with, for example, information gathering either before or during a predation event, and we suggest there is an urgent need for empirical investigation of the costs and benefits of different movement rules, and for an evaluation of the effects of these costs on the potential for different rules to evolve in nature.

Despite the pattern of strong positive frequency dependence in rule success, we do find evidence that changing conditions (predator attack strategy, attack timing and population size and density) shift the balance of rule success (Morrell et al. 2011b; Morrell et al. 2011a). In line with our predictions we find some evidence that peripheral attack strategies are more likely to favour the evolution of complex rules (prediction 1, figure 1), and that those complex rules are more likely to be favoured at later attack times (prediction 2, figure 1). We find no evidence, however, that variation in attack timing supports the coexistence of rules within a population (prediction 3, figure 2). We find that increased population size and lower population density may sometimes improve the

success of simple rules, although this is not always the case (prediction 4, figure 2).

With respect to our prediction that 7NN and LCH are similarly successful, we find partial support. The positive frequency dependence pattern is particularly strong here, with successful invasions of single mutants occurring at low frequencies under the majority of parameters assessed here. However, we see a particular effect of predator attack strategy here in the equal ratios scenario: LCH outperforms 7NN when predators attack from outside the group, while 7NN succeeds when predators attack from within the group. This likely arises because the more complex a rule is, the more effective it is in allowing individuals to reach the centre of the group (Morrell et al. 2011b), where they are protected from peripheral predators, while simpler rules allow for rapid reduction in individual risk when predators attack from within the group (Morrell & James 2008, Morrell et al. 2011a). Thus, 7NN (as the simpler of the two) is favoured when predators attack from within the group, and LCH (as the more complex) when predators attack from outside.

Notice that our consideration of the relative fitness of different strategies considers only within-group differences in expected fitness – and not between-group heterogeneity in predation risk. This is because a key assumption of the selfish herd hypothesis is that there is no group-level variation in predation risk (Hamilton 1971). Our simulations assumed that predators always attack and attacks are always successful, thus any benefits that one individual in a group gains from cover seeking through the selfish herd comes at the expense of

417 increasing predation risk felt by one or more group-mates. This greatly simplifies
418 the scenarios that need to be explored in evaluating the likely evolutionary
419 trajectory of different behavioural rules. Specifically the per-capita average
420 predation risk of individuals in a group is independent of the distribution of
421 strategies played by individuals within that group, and so in considering whether
422 one strategy will prevail evolutionary, we need only consider the comparison of
423 strategies within a group without the added complicity of differential
424 performance of groups with different strategy mixes. Most importantly, if a
425 complex rule rose to numerical dominance within one group, we would not
426 expect this to allow that group to flourish differentially with respect to groups
427 using a simpler rule.

428
429 Our work also points to other ways in which the behaviours underlying group
430 formation through selfish herd effects might usefully be explored. In common
431 with all previous works we consider situationally-unresponsive rules (Hamilton
432 1971; Morton et al. 1994; Viscido et al. 2002; James et al. 2004; Reluga and
433 Viscido 2005; Morrell and James 2008; Morrell et al. 2011b; Morrell et al. 2011a).
434 That is, a given individual employs the same rule regardless of the situation it
435 finds itself in. However, it is easy to imagine that individuals could modify the
436 rule they use to drive their behaviour according to any number of factors:
437 including the size of the group they are in, population density, their position
438 relative to the group centre, time since the predator was first detected,
439 information transfer through the group (Bode et al. 2011b) and behaviours
440 observed in other individuals. As a simple example, an individual might utilise
441 one rule if it perceives that it is one of the first individuals to detect a predator,

442 and another rule if it perceives that it is one of the later-responders. It would be
443 interesting to explore whether a suite of simple situationally-responsive rules
444 can outperform a single more complex but situationally-unresponsive rule.
445
446 Another interesting issue worthy of further exploration is the ecological
447 robustness of rules. Different taxa will experience differences in the intensity and
448 nature of variation in predation scenarios encountered, but strict uniformity of
449 encounter of the type considered in most of our and previous theoretical
450 situations will not be the norm. That is, in the context of the scenario explored
451 here, a given individual may (over its lifetime) experience variation in the
452 number of individuals with which it might potentially form an aggregation, the
453 initial spatial density of those individuals, the time interval between first
454 detection of the predator and completed attack, and the position of the predator
455 relative to prey individuals at the point of first detection. One possible way to
456 cope with such environmental variability would be to have situationally-
457 responsive rules of the type discussed above, and (for example) behave
458 differently when in a low-conspecific-density situation to a high-density one.
459 However, it may be that sometimes conspecific density (in this case) is difficult
460 for individuals to evaluate, and individuals do best of have a “robust” behavioural
461 rule which performs well when evaluated across the frequency distribution of
462 different environmental circumstances likely to be encountered by individuals.
463 Hence, another exciting avenue for the exploration of behavioural rules
464 underlying selfish herd aggregation behaviours is how environmental variation
465 in the types of predator-prey encounters experienced selects for either
466 situationally-responsive strategies of the type discussed above, or robust

strategies that would not be evolutionarily stable in a uniform environment of one fixed type of predator-prey encounter but which offer good performance when evaluated over a frequency distribution of different encounter types.

One last avenue worthy of exploration is error-tolerance. In common with previous works, our evolutionary simulations assume that individuals utilising a particular rule can gather all the information on conspecifics needed for the implementation of that rule without error. This is likely to be a simplification of reality, and it would be interesting to explore how the introduction of different plausible error structures influences the relative performance of different rule types. For example, it may be that errors in the evaluation of another individual increase with increasing distance of that individual from the focal individual. If errors are common and essentially independent when evaluating information on different individuals this may select for more complex rules that obtain stochastic cancellation of such errors (the “many wrongs principle” – discussed in the literature on in group navigation decisions e.g. Simons 2004; Hancock et al. 2006; Biro et al. 2006; Codling et al. 2007; Faria et al. 2009). Additionally, errors may be influenced by environmental factors such as ambient light levels. This may offer the opportunity for empirical testing of theoretical predictions about how behavioural rules might be expected to change in response to increased error rates in information gathering (say as induced experimentally by lowering ambient light levels).

Acknowledgements

491 Paul Bennett and Dick James wrote the original code on which this work was
492 based, Steve Moss assisted with additional programming, and Dick James
493 provided useful discussions.

494

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Figure legends:

Figure 1: Number of simulations resulting in fixation for the simpler (white shading), more complex (grey shading), or neither (black shading) rule, for 3 scenarios (columns) and three movement rule combinations (rows). Each column represents a different invasion scenario: a simple rule invading a more complex population (left hand column, a, d and g), a more complex rule invading a simple population (right hand column, c, f and i), and a situation where both rules begin at equal frequencies (central column, b, e and h). Each row represents a different pairwise combination of movement rules: NN v 3NN (top row, a-c), NN v LCH (middle row, d-f) and 3NN v LCH (bottom row, g-i). In each case the simpler rule is specified first (see table 1). The horizontal dashed line represents the expected proportion of simulations in which the simpler rule would be expected to fix if predation were random with respect to movement rule, ** indicates significant deviation from random expectation at $p < 0.001$, NS indicates no significant deviation from random expectation. Each panel shows the outcome for 3 different fixed attack times (20, 50 and 100 timesteps) when the predator attacks from within the group (left of the thick vertical line) and from outside the group (right of the thick vertical line). Other parameters: $N = 20$, $d = 4$.

Figure 2: Number of simulations resulting in fixation for the simpler (white shading), more complex (grey shading), or neither (black shading) rule, for three movement rule combinations and when predators attack from within the group. Each panel shows both fixed (left of the thick vertical line) and variable (right of

the thick vertical line) attack timings for populations of $N = 20$ (left column, a, c, e) and $N = 50$ (right column (b, d, f). Three combinations of rules are shown, both begin at equal frequencies in the population: top row: NN v 3NN, middle row: NN v LCH, bottom row: 3NN v LCH. Results are shown at three different population size/density combinations: left column: $N=20$, $d=4$ (baseline), middle column: $N=50$, $d=4$ (increased population size) and right column: $N=20$, $d=10$ (increased population density). The horizontal dashed line represents the expected proportion of simulations in which the simpler rule would be expected to fix if predation were random with respect to movement rule, ** indicates significant deviation from random expectation at $p < 0.001$, NS indicates no significant deviation from random expectation.

Figure 3: Number of simulations resulting in fixation for the 7NN (white shading), LCH (grey shading), or neither rule (black shading) for pairwise contests between 7NN and LCH, for 3 invasion scenarios (rows) and three population size and density combinations (columns). The left column shows data for $N=20$, $d=4$ (a, d, g). In the middle column group size is increased to $N=50$ while keeping $d=4$, and in the right column density is increased to $d=10$ while keeping $N=20$. The top row shows a 7NN mutant against and LCH population, while the middle row shows the results from equal starting frequencies, and the bottom row shows an LCH mutant in a 7NN population. Each panel shows both fixed and variable attack times (x-axis) and predators that attack from inside (left hand columns) and outside (right hand columns) the group (separated by the thick vertical line). The horizontal dashed line represents the expected

653 proportion of simulations in which the simpler rule would be expected to fix if
654 predation were random with respect to movement rule, * indicates significant
655 deviation from random expectation at $p < 0.05$, ** at $p < 0.001$ and NS indicates
656 no significant deviation from random expectation.

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659 **Tables and Figures**

660 **Table 1:** Movement rules

Rule	Description
NN	Each prey individual moves directly towards its closest neighbour (Hamilton 1971). This is the simplest rule we consider, and is used in testing predictions 1-4.
3NN	Each individual moves towards the average location of its three closest neighbours (Morton <i>et al.</i> 1994).
7NN	Each individual moves towards the average location of its seven closest neighbours (Morton <i>et al.</i> 1994). This rule is used to test prediction 5 only.
LCH	Each individual takes into account the location of up to 20 closest neighbours, although closer individuals have a stronger influence on movement direction, described by the perception function $f(x) = \frac{1}{1 + kx}$ where k=0.375 and x is the distance from the focal individual to each neighbour. Individuals thus move towards the densest areas of the group (Viscido <i>et al.</i> 2002). This is the most complex rule we consider.

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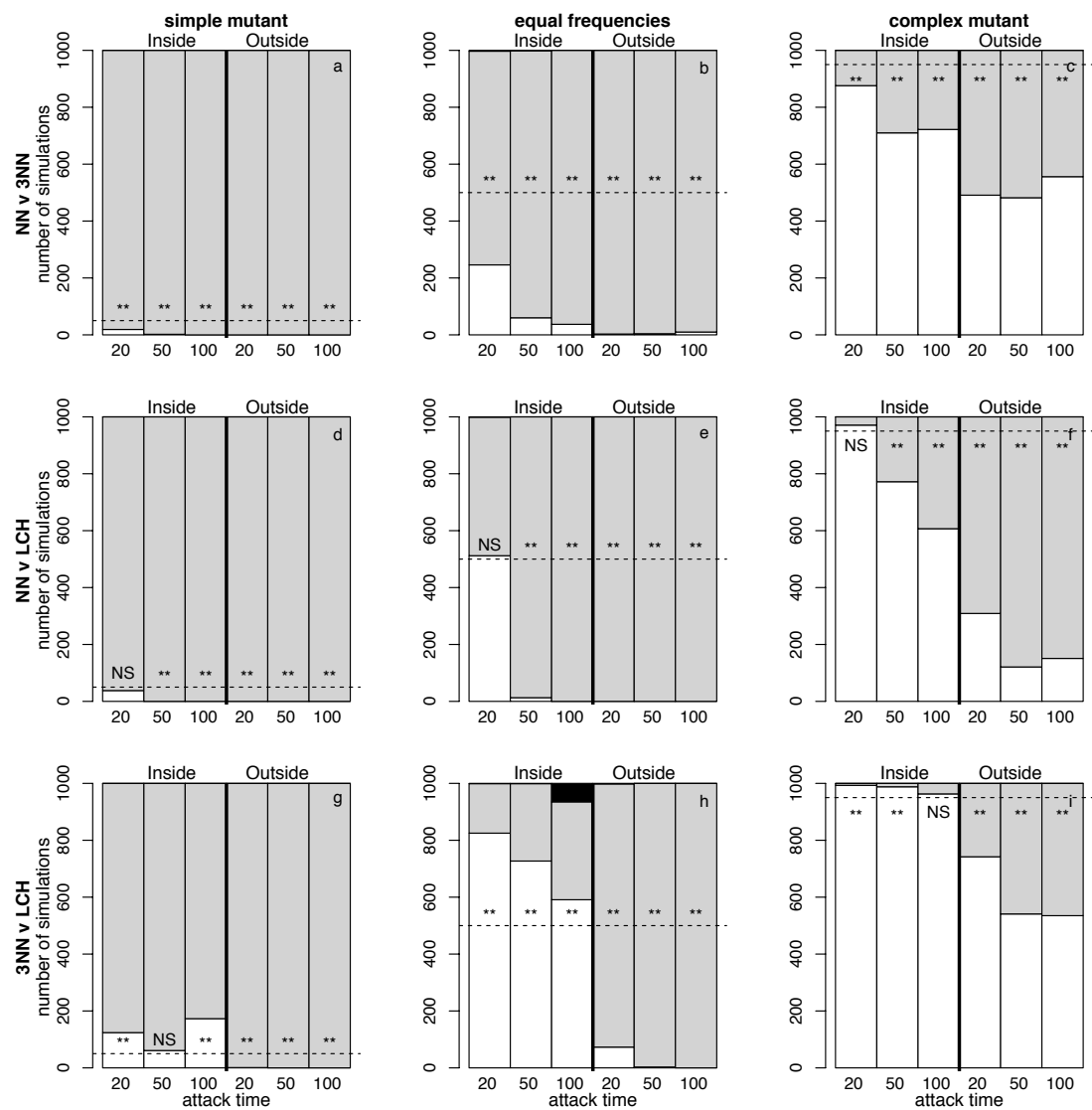
663 **Table 2:** Summary of predictions and results

664 (Please see the additional document for this table, which is formatted as

665 landscape)

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667 Figure 1

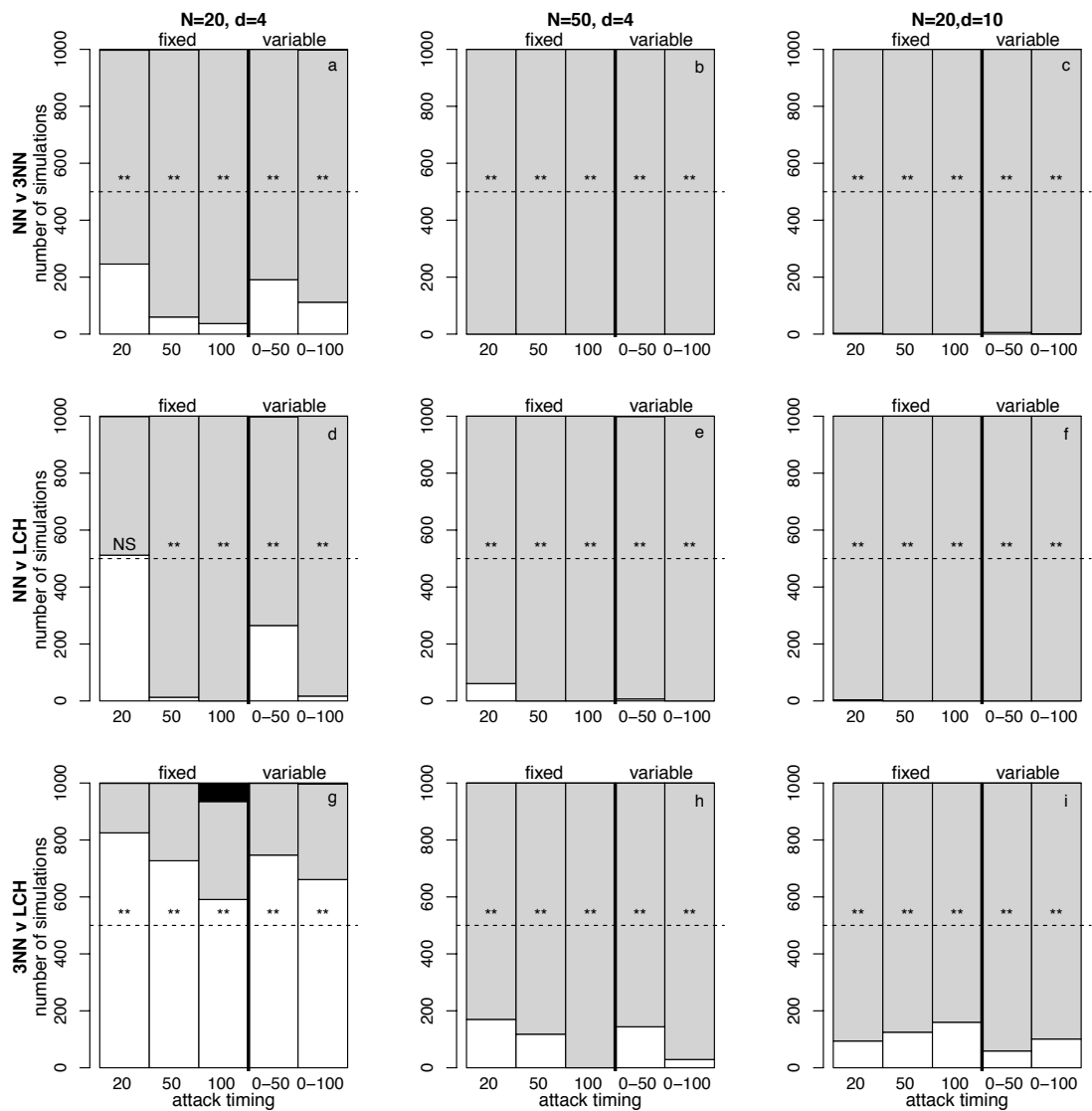


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671 Figure 2



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